AN OPTIMIZED CONVOLUTIONAL NEURAL NETWORK-BASED ENSEMBLE CLASSIFICATION AND REGRESSION FRAMEWORK FOR CLASSIFYING THE STAGES OF DIABETIC RETINOPATHY

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1. INTRODUCTION

Deep learning (DL) techniques offer optimized solutions in a broad spectrum of real-world applications, including medical image analysis, autonomous vehicle control, fraud detection, and many other domains. Deep learning progresses from machine learning models where the learning data is associated with the task-based methods. Deep learning has proved to be effective in handling complex image representation. Recently, the insights gained from the deep learning techniques have aided the health care industry especially in the medical imaging sector. Medical imaging is one of the high priority areas for potential research with computer aided medical devices especially for disease diagnosis, disease monitoring and treatment. This study focuses on accurately classifying the stages of an eye disease, Diabetic Retinopathy. Diabetic Retinopathy (DR) is an ocular condition impacting the eyesight of individuals with diabetes, potentially resulting in blindness during its advanced phases. The growing global population of individuals with diabetes highlights the need for the improvement and development of new techniques in the current era. Many computer aided diagnostic systems were developed but there exists a need for significant performance improvement in classifying the stages of DR.

An automatic DR screening on retinal images using deep learning approaches was proposed (Fahman Saeed *et al.*, 2021). A two-step transfer learning technique was utilized, involving the Convolutional Neural Network (CNN) for the screening of DR in retinal images. Considering the areas of interest within the lesions, a pre-trained CNN was tuned in the first layer and the lower-level layers are learnt using the local structures. The complete layer was encoded with features and the new complete layer was replaced with the principal component analysis. This process minimized the complexity and over fitting issues. DR features were detected, and gradient boosting classification layer was included. This technique proved ineffective when applied to low-saturation fundus images. Additionally, reinitializing the first CNN layer led to the loss of information in non-lesion areas.

A computer-aided diagnosis system employing DL techniques was presented for screening the pathological abnormalities of DR disease (Eman AbdelMaksoud *et al.,* 2020). Depending on the multi-label classification, a system customised for EffecientNet model to identify the DR disease in early and advanced grades using transfer learning. In this technique, to expand the image dataset, basic augmentation operation, cropping was performed. This operation led to the loss of information around the retinal edges. A novel neural network model was presented for extracting characteristics from retinal images to classify DR. (Gayathri S *et al.,* 2020). The supervised learning-based classifiers were used in this study for the classification of Kaggle and other dataset images. The classification efficiency was assessed by recall, accuracy, sensitivity, precision, false positive rate and specificity. In this proposed technique, the tiny lesions were not detectable in the initial stages of DR diagnosis.

An automated DNN for classifying DR disease was proposed using deep transfer learning model (Hassan Tariq *et al.,* 2021). Some of the pre-trained models were used in this study The DR images are collected, labeled and treatment approach is automated which assists the patients to undergo therapies. The custom dataset used in this work limited the generalization ability when images with different characteristics were used. Image segmentation and blood vessels generation by geometric processing, thresholding, edge identification, and AHE was presented (Sangeethaa S N *et al.,* 2018). The DL model was developed and trained on a dataset containing imbalanced classes. This has produced biased results in classifying mild and moderate DR images. To bridge the gap between these techniques, this research proposes new techniques in DR disease classification using deep learning methods to address the aforementioned issues. The research problem is articulated as below.

"Due to the presence of imbalanced classes in the retinal image database and the lack of high-level image features hinders the classification performance of diabetic retinopathy, highlighting the need to address these challenges for significant improvement."

To address the problem statement, the primary objective of the research is:

- To improve the classification performance of Diabetic Retinopathy stages using an optimized convolutional neural network-based ensemble classification and regression framework.

Further, to meet out the above-mentioned primary objective, the following specific objectives are set forth herein below:

- To develop image preprocessing technique that eliminates retinal fundus image noises to improve the classification performance.
- To deploy augmentation strategies that address class imbalance issues to improve the classification performance.
- To enhance Convolutional Neural Network (CNN) architecture that captures subtle diabetic retinopathy image features to improve the classification performance.
- To develop an enhanced optimization technique that searches for the best set of CNN hyper-parameters to improve the classification performance.

2. RESEARCH METHODOLOGY

Computer vision applications utilize deep learning concepts, which have become increasingly popular, especially for processing large volumes of data. However, they demand a significant amount of resources. In this presented work, retinal fundus images from two different benchmark datasets such as APTOS and IDRiD were used. The configuration settings include Intel Core i7 7^{th} generation processor, 2.7 GHz, 1TB SSD, 16 GB RAM, and windows 10 operating system. Initially, a two-stage image preprocessing framework was proposed, consisting of image denoising and augmentation. A hybrid wavelet-based image denoising technique, DWT_K-SVD, along with Contrast Limited Adaptive Histogram Equalization (CLAHE) was employed to eradicate gaussian and salt-and-pepper noises. Basic augmentation operations were then performed on the preprocessed images to expand the dataset. Three deep learning-based CNN models such as Multi-Scale Attention-based Residual Network with Gradient Boosting (MSA-ResNetGB), Special Generative Adversarial Network with Ensemble Classification Regression (SGAN-ECR) and SGAN with Optimized ECR (SGAN-OECR) were developed as part of this research. The base network for these three proposed models is the Residual Network (ResNet-32). Retinal fundus image feature extraction and classification tasks are performed by the proposed CNN models.

2.1 Preprocessing and Augmentation

As gaussian and salt and pepper noises are the predominant noises present in Retinal fundus images, it is required to eliminate such noises to achieve better DR diagnosis. However, the task of eliminating noise from these images poses a challenge encountered by all researchers. (Radhamani V *et al.*, 2021). This section aims to mitigate the noise impact especially on retinal images. Wavelet transform has gained significant popularity in various domains of image processing, with a notable emphasis on its application in medical image denoising. The proposed Discrete Wavelet Transform with k-singular value decomposition (DWT_k-SVD) method is a hybrid technique which uses the wavelet coefficients to de-noise the distorted image from the sparse representation which is learnt from the redundant dictionary. The k-SVD (Michal Aharon *et al.*, 2006) de-noising technique initiates k-means clustering and SVD. A dictionary-based technique is used for learning that generates a sparse representation and employs an overcomplete dictionary.

In this approach, adaptive gaussian thresholding is used to address the issue of variable noise levels within an image. Images often contain regions with varying levels of noise, and this adaptive thresholding approach helps in preserving image details while effectively reducing noise. The Gaussian thresholding method adapts the threshold to the local characteristics of the coefficients, making it a powerful denoising technique.

Also, GOMP algorithm is applied to find the sparse codes for the thresholded coefficients. GOMP is a greedy algorithm that iteratively selects the most promising atoms from the dictionary to represent the data. This process efficiently captures the significant features in the data while reducing the number of coefficients used for representation. It efficiently finds a sparse representation of the data, which is crucial for denoising. By using a sparse representation, it reduces the impact of noise in the coefficients while retaining essential image information. The error is minimized as the result of the operation and the image patches are averaged. This process is repeated until the image gets de-noised. At last, IDWT is employed on the coefficients to generate the de-noised image. The denoised image is further improved by applying CLAHE. Then, basic image augmentation operations such as random rotation, horizontal and vertical flip and translation were then performed on the preprocessed images to expand the dataset. The pseudo code for hybrid DWT_K-SVD technique is presented.

Pseudo Code: A Hybrid DWT_K-SVD technique for image denoising

Input: APTOS & IDRiD dataset images

Output: Denoised images

Begin

Step 1: Data acquired from the APTOS & IDRiD image dataset

Step 2: Apply Discrete Wavelet Transform (DWT) that uses Daubechies 2 (db2) wavelet to decompose the input image into its wavelet coefficients

Step 3: Use adaptive gaussian thresholding to wavelet coefficients

- **Step 3.1:** Calculate the standard deviation of coefficients
- **Step 3.2:** Calculate the threshold based on the standard deviation
- **Step 3.3:** Apply the threshold to coefficients

Step 4: Sparse Coding using Greedy Orthogonal Matching Pursuit (GOMP)

- **Step 4.1:** Dictionary is initialized and the size can be adjusted
- **Step 4.2:** Sparsity level is defined, indicating the number of non-zero coefficients that represent each thresholded coefficient
- **Step 4.3:** The GOMP algorithm is applied to find the sparse codes for the thresholded coefficients. This iteratively selects the most promising atoms from the dictionary to represent the data.

Step 5: Apply Inverse DWT (IDWT) on noise-reduced wavelet coefficients to reconstruct the denoised image. The same wavelet type (db2) is applied.

End

2.2 Feature Extraction and Classification

Feature extraction and classification are performed using CNN-based deep learning models. The proposed models aim to extract more relevant and subtle image features required for effective DR disease classification based on severity levels.

2.2.1 MSA-ResNetGB Model

An adaptive residual neural network model named ResNetGB, which incorporates Gradient Boosting (GB), has been developed to synergize with the Multi-Scale Attention (MSA)

approach named as MSA-ResNetGB. This model primarily focused on subtle image features in different regions of the retinal fundus image to provide better performance in classifying DR disease. A Pretrained Residual Neural Network (ResNet-32) has been used as a base network. The pseudo code for the MSA-ResNetGB model is given below.

Pseudo code: MSA-ResNetGB model for classifying the stages of DR

Input: Retinal images from APTOS & IDRiD dataset $I_1, \ldots, I_n$

Output: DR stage classification (0-4)

Begin

Step1: Labeled RF images are obtained and split into training and testing.

Step2: With the help of the ResNetGB encoder, the acquired training images are embedded into the high-level representational space. Equation (5.1) shows the interpretation of tensor F_{ec} generation:

$$F_{ec} = G(\theta_1;1) \tag{1}$$

Step 3: The attention strategy is included into the multi-scale feature interpretation.

Step 4: The discriminative ability of high-level feature interpretation is improved; then the point-wise convolution among the pyramid representations is used.

Step 5: Generate the attention tensor $\mathcal{A}$. Equation (5.2) shows the attention tensor:

$$\mathcal{A}^{h\times w\times 64} = \left(F_{all}^{h\times w\times 4c} * \mathbb{K}_{pw}\right) \tag{2}$$

Step 6: Acquire the global interpretation by Global Mean Pooling (GMP) and create the feature interpretation vector F. Equation (5.3) shows the feature interpretation vector:

$$F^{1\times 1024} = \frac{GMP\left(\sigma\left(F^{h\times w\times c} \odot \mathcal{A}^{h\times w\times 1}\right)\right)}{GMP(\mathcal{A}^{h\times w\times 1})} \tag{3}$$

Step 7: Use the PCA layer to transform the feature vectors into the required outcomes.

Step 8: Use GB classifier to train. Estimate the loss factor L (θ, φ) and modify the training variables.

Step 9: Apply the testing set on MSA-ResNetGB model and categorize according to their DR levels.

End

A high-level interpretational space within the encoder network is utilized to embed the Retinal image, facilitating the fusion of mid and high-level data to enhance interpretability. The extracted image characteristics are fed into the classifier to classify the retinal image based on DR stages. This is accomplished by creating a Multi-Scale Feature Pyramid (MSFP) to represent the RF image across different locations. Also, to further boost the discriminative capacity of feature interpretation, the MSA method is applied within the high-level interpretational space.

In this proposed model, first, the pre-processing and augmentation strategies are applied to the retinal dataset to regularize the image and decrease the image noise as discussed in the sub-section 2.1. The processed images were then used to train the MSA-ResNetGB model to categorize the DR stages. The MSA-ResNetGB model comprises of four components: the ResNetGB as an encoder component that transforms the retina image into a high-level representation space. Next is the multi-scale feature extraction and analysis component, then a Multi-scale attention tool, and finally the decoder component to produce the DR score and it's classified into different classes of DR classification units. The performance analysis of the MSA-ResNetGB model is discussed in the section 3, Results and discussion.

2.2.2 SGAN-ECR Model

A novel deep learning model, SGAN-ECR was developed to create high-contrast retinal fundus images, to provide better generalization ability for classifying DR stages based on severity and to enhance the classification performance. The SGAN consist of pixel-2-pixel GAN with UNet++ generator and a patch-GAN discriminator. To train the shape of dissimilarities of the retinal fundus images pixel-2-pixel GAN generator is used and to enhance the image segmentation with accurate local contrast patterns a patch-GAN discriminator is used. In the SGAN model, high contrast synthetic retinal images are generated which are utilized for training the MSA-ResNet regression and classification structures. The inter-dependencies among the various stages of DR severity are learnt in the regression structure. The discriminative features of the fundus images are learnt in the classification structure. Finally the characteristics are concatenated and fed into the MLP classifier for classification. Totally, 4500 synthetic images are generated by SGAN from both datasets to mitigate the class imbalance. The pseudo code for the SGAN-ECR model is provided below.

Pseudo code: SGAN-ECR model for classifying the stages of DR

Input: Retinal Fundus images from APTOS & IDRiD dataset along with SGAN generated synthetic images $I_1, \dots, I_n$

Output: DR stage classification (0-4)

Begin

Step 1: Get the dataset images for DR grade classification;

Step 2: Categorize the image database into training and test set;

Step 3: Execute SGAN model on training set to generate the synthetic RF images;

Step 4: Incorporate the images into the original training dataset to balance the dataset classes;

Step 5: Initialize ResNetGB encoder parameters such as learning rate, iteration count, $t \leftarrow 0$, maximum accuracy test set $max_{acc} \leftarrow 0$ and maximum iteration T_{max};

$while(t < T_{max})$; $t \leftarrow t + 1$;

$for(training\ set)$

Train MSA-ResNet classification model and MSA-ResNet regression model;

Calculate loss factor using Equation (5.3) & (5.4); adjust the training variables;

MLP classifier applied to get the result of the trained classification model;

$end\ for$

Step 6: Categorize test images according to the levels of DR severity using the trained model.

Step 7: Determine the classification accuracy (acc) on the test set;

$\boldsymbol{if}(a > max_{acc})$

$max_{acc} \leftarrow acc$;

Step 8: Set the optimal training variables of ResNetGB;

End if;

End while;

End

The SGAN generated synthetic retinal images along with the benchmark images are used for training MSA-ResNet classification and Regression model. To obtain the subsequent feature maps, the MSA employs a high level feature map with multiple scales that are concatenated with the attention maps. The MSA-ResNet regression model is equipped to categorize the different

levels of DR severity by simultaneously learning the progressive features between DR severity levels. The dependency among the DR grade levels rely on the severity stages such as higher and lower.

The output probability of all classes ranges between 0 and 1 in regression model. There are five probability scores associated with five DR grades in the regression model. Finally single outcome will be produced in the regression model. The model is trained with the result labels like 0 indicates normal, 0.2 indicates mild DR, 0.4 indicates moderate DR, 0.6 indicates severe DR and 0.8 indicates proliferative DR. The classification model with five different classes, ranging from class 0 to class 4, each representing different levels of DR severity, including normal, mild DR, moderate DR, severe DR, and proliferative DR (PDR). The learnt features of classification and regression model are concatenated and then fed into the classification layer. The final DR disease classification is obtained using the MLP classifier instead of GB classifier. The evaluation of the SGAN-ECR model's performance is detailed in Section 3, Results and discussion.

2.2.3 SGAN-OECR Model

The proposed SGAN-OECR model for DR stage classification focused on optimizing the hyper-parameters of SGAN-ECR model for maximizing the classification performance of SGAN-OECR model based on the DR severity levels. In SGAN-ECR model, realistic synthetic retinal images were generated using SGAN. The dataset images along with SGAN generated images were used for training MSA-ResNet classification and regression structure. The learnt features from classification and regression model are then concatenated and classified using MLP classifier, based on DR severity levels. The SGAN-ECR model was found to be effective as the model was trained on more realistic images that had varied features. To enhance classification accuracy even further, the hyper-parameters of SGAN-ECR model is optimized using Enhanced Mine Blast Algorithm (EMBA).

EMBA is used to optimize the hyper-parameters of the SGAN-ECR model. The hyper-parameters that are considered for optimization are learning rate, momentum, batch size, convolutional layer, kernel size, activation function, filter size, dropout and the number of epochs. The pseudo code for the SGAN-OECR model is provided below.

Pseudo code: SGAN-OECR model for classifying the stages of DR

Input: Retinal Fundus images from APTOS & IDRiD dataset along with SGAN generated synthetic images $I_1, \dots, I_n$

Output: Different DR severity levels

Begin

Initialize primary parameters N_d,γ, ε, $\mathcal{ub}$, $\mathcal{lb}$,p_{max};

$While(p < P_{max})$; $P \leftarrow p + 1$;

Step 1: Initialize the initial shot location.

Step 2: Generate additional shrapnel fragments and adjust their positions; Calculate the distance and direction of the shrapnel pieces.

Step 3: Estimate the fitness function and update the distance and direction of shrapnel pieces using MSA-ResNet structures. The greatest fitness value is regarded as the optimal location containing shrapnel fragments.

Step 4: The location of the shrapnel pieces is enhanced by exploration and exploitation phase. The process stops, if the terminating criteria is met else shrapnel pieces process is generated;

Step 5: The best location of the shrapnel pieces is stored else replace the location of shrapnel pieces with another location;

end while;

Step 6: Chose the highest fitness value with best shrapnel piece location. Get the trained SGAN-OECR model.

Step 7: Apply the testing set on SGAN-OECR model and categorize according to their DR levels.

End

EMBA is inspired from the landmine detonation process. During landmine explosion, the shrapnel scatters and collides with other landmines within the blast radius. This process eliminates the other landmines. Therefore, to determine the best solution, the initial blasting point is pinpointed, where the collision volume is generated to clear the mines already present in that specific region. The primary population is taken as the reference solution. Subsequently, the first explosion is initiated, and the population size is denoted by the quantity of shrapnel

fragments obtained by the initial detonation (Ali Sadollah *et al.*, 2013). Population-based metaheuristic algorithms typically consist of both a global search phase for exploration and a local search phase for exploitation (Ali Sadollah *et al.*, 2014). The dispersal of shrapnel to several new positions is the exploration phase and the utilization of existing resources in the identified locations is the exploitation phase. The evaluation of the SGAN-OECR model's performance is detailed in Section 3, Results and discussion.

3. RESULTS AND DISCUSSION

The presented research work uses two different image datasets, APTOS and IDRiD. Initially, preprocessing methods such as the median filter (MF), Wiener filter (WF), DWT, and DWT_K-SVD were applied to both datasets. The proposed hybrid DWT_K-SVD method effectively eliminated gaussian and salt-and-pepper noises present in the retinal fundus images. CLAHE was applied to denoised images produced using MF, WF, DWT, and DWT_K-SVD, and their performances were assessed using Peak Signal-to-Noise Ratio (PSNR), Signal-to-Noise Ratio (SNR), and Structural Similarity Index Measure (SSIM) metrics. Tables 1 and 2 show the performance evaluation of preprocessing techniques on the APTOS and IDRiD datasets.

Table 1. Performance Evaluation of Preprocessing Techniques on APTOS dataset

Performance Metric	Preprocessing Techniques on APTOS Dataset			
	Median Filter + CLAHE	**Wiener Filter + CLAHE**	**DWT + CLAHE**	**DWT_K-SVD + CLAHE**
PSNR (dB)	40	42	44	47
SNR (dB)	65	68	70	73
SSIM	0.78	0.81	0.85	0.91

Table 2. Performance Evaluation of Preprocessing Techniques on IDRiD dataset

Performance Metric	Preprocessing Techniques on IDRiD Dataset			
	Median Filter + CLAHE	**Wiener Filter + CLAHE**	**DWT + CLAHE**	**DWT_K-SVD + CLAHE**
PSNR (dB)	41	42	43	46
SNR (dB)	69	71	72	74
SSIM	0.81	0.85	0.89	0.92

Due to the hybrid nature of DWT_K-SVD, this technique outperformed the other techniques in all the considered metrics on both datasets. The performance evaluation of the deep learning models such as MSA-ResNetGB, SGAN-ECR and SGAN-OECR on APTOS and IDRiD datasets is shown in Table 3 and Table 4.

Table 3. Performance Evaluation of Proposed Deep Learning models on APTOS dataset

Performance Metric	Classification Performance on APTOS Dataset		
	MSA-ResNetGB Model	SGAN-ECR Model	SGAN-OECR Model
Accuracy (%)	94.40	97.81	98.21
Precision (%)	94.53	95.95	98.12
Recall (%)	94.40	95.98	96.42
F1-Score (%)	94.43	96.90	97.86

Table 4. Performance Evaluation of Proposed Deep Learning models on IDRiD dataset

Performance Metric	Classification Performance on IDRiD Dataset		
	MSA-ResNetGB Model	SGAN-ECR Model	SGAN-OECR Model
Accuracy (%)	94.18	96.12	97.09
Precision (%)	91.48	96.31	97.37
Recall (%)	91.57	93.73	96.42
F1-Score (%)	91.45	94.77	96.86

On both APTOS and IDRiD datasets, the SGAN-OECR model produced better results compared to MSA-ResNetGB and SGAN-ECR models in all considered metrics. This is due to the fact that SGAN-OECR is the optimized model that overcomes the limitations found in the other two models. To be more specific, the performance results of all three models were higher on the APTOS dataset compared to the IDRiD dataset. This can be attributed to the fact that the APTOS dataset includes more images than the IDRiD dataset. The more samples used for training, the better the overall performance.

4. CONCLUSION

This study has focused on Diabetic Retinopathy (DR) stage classification, which aids in the improvement of the decision-making process. Identifying DR at an early stage and providing

precise treatment can prevent blindness. Retinal fundus images are often affected by gaussian noise and salt-and-pepper noise, which can obscure subtle image features necessary for accurate diagnosis of retinal diseases. In this study, two different image datasets, APTOS and IDRiD were used and a two-stage image preprocessing framework was developed, consisting of image denoising and augmentation. A hybrid wavelet-based image denoising technique, DWT_K-SVD, was proposed and proven to be effective in eliminating gaussian noise compared to existing techniques. Following denoising, contrast enhancement using CLAHE was applied to further improve image quality. Basic augmentation operations were then performed on the preprocessed images to expand the dataset. Three deep learning-based CNN models were developed as part of this research. The first model, MSA-ResNetGB, focused on extracting subtle characteristics like soft and hard EXs, MAs, and HEs in different regions of the retinal fundus image. This model prioritized information related to lesions and relevant structures using a Multi-Scale Attention-based Residual Network. It proved to be effective in classifying DR stages based on severity levels. The second model, SGAN-ECR, was designed to generate high contrast and diverse images for training. It also demonstrated better generalization ability as it employed ensemble classification and regression models for classifying DR stages. The third model, SGAN-OECR, focused on optimizing the hyper-parameters of the SGAN-ECR model using the enhanced MBA technique, which improved the classification performance of DR disease. Thus, it can be concluded that this research work has successfully achieved its objectives with a focus on improving the classification performance.

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